Applied Mathematics & Information Sciences
An International Journal

http://dx.doi.org/10.12785/amis/090141

Single Sample Face Recognition using LGBP and Locality Preserving Discriminant Analysis

Minghai Xin[1,2,*], *Yali Zhou*[1] *and Jingjie Yan*[1]

[1] Research Center for Learning Science, Southeast University, Nanjing, 201196, China
[2] School of Computer Science and Technology, Huaqiao University, Xiamen, 361021, China

Received: 10 Apr. 2014, Revised: 11 Jul. 2014, Accepted: 12 Jul. 2014
Published online: 1 Jan. 2015

Abstract: On single sample condition, current face recognition algorithm yields serious performance drop or even fail to work, therefore a face recognition algorithm based on LGBP and locality preserving discriminant analysis (LPDA) was proposed. Image enhancement and geometric transformation were firstly introduced to single sample face image for face reconstruction, making reconstruct image and original counterpart as a new training sample set. The feature of LGBP was then adopted for face image feature extraction. Afterwards LPDA was used for feature dimension reduction. Classification was finally accomplished by Euclidean distance-Nearest Neighbour Classifier. The validity of this algorithm was testified by ORL database, Yale database and FERET database.

Keywords: Face Recognition, Single Sample, Local Gabor Binary Pattern.

1 Introduction

Face recognition algorithm has becoming the research focus in the field of pattern recognition for the past decades, but the majority of the current face recognition algorithms are dependent on adequate quantity and typical training sample in the systems. Jain et al[1] indicated that sufficient generalization ability can only be acquired by intelligent system if sample number is an order of magnitude higher than sample dimension. Another decisive factor is the representativeness of samples which implies that at least one training sample, collected under the same condition with testing image, exists in training set. Owing to difficulty in collection of this sort of training samples, the research of single sample face recognition has becoming a significant sub-subject in the field of face recognition. The single sample face recognition[2], of which training sample set was single image per person, demanding the identification of test image using face recognition system from face database stored with only one identified individual image. It is relatively easy for collection of training sample since only one image per person is needed. Moreover, the low storage and processing cost for single image per person can effectively reduce the consumption of system resource. Therefore single sample face recognition has gradually becoming the research focus on account of the above mentioned advantages, although big challenges still exist for the moment. Single sample face recognition is generally divided into 4 components, namely face reconstruction, feature extraction, feature dimension reduction and classification recognition. Single sample face reconstruction relied on geometrical feature techniques, sample expansion techniques and image enhancement techniques. The major research findings based on geometrical feature technique were as follows: Bledsoe et al. devised an off-line eye detector for accurate positioning of eye area [3]; Brunelli et al. developed a recognition system for automatic collection of geometrical feature points [4]. Manjunath et al. composed topological graphs for recognition by collecting feature points, with Gabor wavelet representation for face [5]. The basic idea of sample expansion technique is the synthesis of original samples by adopting various techniques. The techniques mentioned by [6,7,8,9, 10]can be generally classified into two types: multiple virtual image of single sample was obtained by 2D face reconstruction using mirror, translation, rotation and scaling; a new virtual sample was synthesized by 3D face reconstruction through the simulation of the variation of posture, expression, light. Image enhancement of single sample is implemented by image enhancement techniques

* Corresponding author e-mail: xin_minghai@163.com

with the purpose of highlight the primary and favorable feature with restraining the secondary and unnecessary or even system-interferential information. Wu and Zhou proposed a Projection Combined Principal Component Analysis ((PC)2A) [11]; On that basis, Chen added second order image projection and put forward Enhanced Projection Combined Principal Component Analysis(E(PC)2A) [12]. Furthermore Zhang et al. presented Singular Value Decomposition (CVD) and image reconstruction techniques with wavelet decomposition [13]. The feature extraction of single sample face recognition is of vital importance to the performance of recognition system. Current features used for face recognition mainly consist of geometrical feature, mixing, sequence feature and etc. Among them, Gabor feature representation of textural feature represents frequency spectrum of signals in local time domain and frequency domain, and enhances the low frequency high frequency of image. Gabor feature resembles the visual system of human being, from the visual aspect. Currently Gabor wavelet has found its popular application to handwriting feature recognition, texture segmentation, fingerprint recognition, face and expression recognition. The typical recognition techniques include Gabor wavelet multilayer neural network [14], the discriminatory analysis of Gabor feature [15], and the Independent Component Analysis of Gabor feature [16]. Meantime, the research findings from Lyons et al. demonstrated the effective feature of face image encoding [17] by Gabor feature. Nevertheless, Gabor feature, generally multidimensional vector, is once brought into sorter for recognition, not only huge calculation will be produced, but also side effects on sorting may result due to its large redundant information. As a consequence, appropriate feature dimension reduction is indispensable. Generally, feature dimension reduction techniques can be classified into linear technique and nonlinear technique. Dimension reduction algorithms can be divided into local type and global type depended on whether considering of the local geometric construction of data or not. The representative global type dimension reduction algorithms are such as PCA, LDA, ISOMAP and etc. While local type Dimension reduction algorithms comprise of manifold learning algorithms such as LLE and LE, and the corresponding linearization versions like Neighborhood Structure Preserving Embedding (NPE) [18] and Locality Preserving Projections (LPP) [19]. The LPP has found its application in face recognition thus brought about Laplace faces. In the field of pattern recognition, the performance of LPP precedes that of classical PCA and LDA, but LPP algorithm is an unsupervised linear learning technique, without utilization of class information of samples. On the basis of LPP, this article proposed LPDA which defined the weighting matrix of intra-class adjacent map and inter-class adjacent map with addition of the class information after face reconstruction sample, thus face recognition rate got improved. Firstly, sample reconstruction of single sample face image including 3 images from image enhancement and 5 images from geometric transformation combined with original training sample image, training sample set expanded to 9 images which composed a new sample set. The LGBP feature of every face image from sample set was subsequently collected and then dimensional reduction for high-dimensional LGBP eigenvector was implemented by LPDA. Lastly, the Classification for eigenvector with reduced dimensions was conducted by KNN algorithm. Experimental results from FERET Database, ORL Database and Yale Face Database demonstrate the validity of this algorithm on single sample face recognition.

2 Face Reconstruction Based on Image Enhancement and Geometric Transformation

2.1 Projection Combined Principal Component Analysis

Principal component analysis was an image enhancement technique proposed by Wu and Zhou [11], expecting maximized information collected from single sample face image for recognition. $P(x,y)$ was speicified as the gray value of point (x,y) in an image with size of $N_1 \times N_2$, and then the horizontal projection and the vertical projection of this image were specified $V(x) = \sum_{y=1}^{N_2} P(x,y)$ and $H(y) = \sum_{x=1}^{N_1} P(x,y)$ respectively, which in some extent reflect the distribution feature of major local area in the face image as shown in Fig.1(a). Projected image was defined as $M_p(x,y) = V(x) \times H(y)\sqrt{P}$, where $\bar{P}$ average gray level of projected image, this projected image was superposed by Eqs.(1) onto the original face image, called first order projection, and thus original information was enhanced.

$$P_\alpha(x,y) = \frac{P(x,y) + \alpha M_P(x,y)}{1+\alpha} \tag{1}$$

where α is assembly parameter, (generally $0 \leq \alpha \leq 1$). It can be found from Fig. 1(c) that the local noise contained in enhanced image was highly reduced and the image became much smoother.

2.2 Enhanced Projection Combined Principal Component Analysis

Chen et al.[12], presented an improved algorithm-E(PC)2A on the foundation of (PC)2A. $I(x,y) = P^2(x,y)$ was defined, and the horizontal projection $V_2(x) = \sum_{y=1}^{N_2} I(x,y)$ and the combined projection

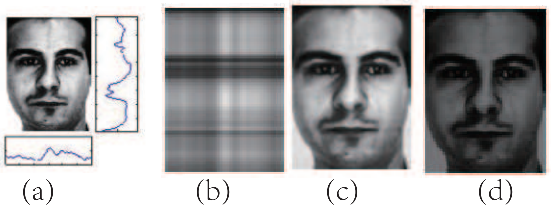


Fig. 1: Combination projection, enhanced combination projection procedure chart [15]

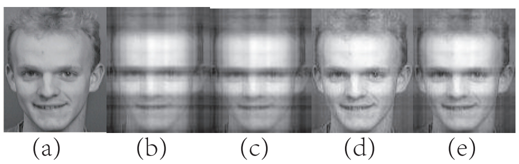


Fig. 2: Original image projection bitmap and combined projection

$H_2(y) = \sum_{x=1}^{N_1} I(x,y)$ of $I(x,y)$ were obtained. Where $M_p'(x,y) = V_2(x) \times H_2(y)\sqrt{P}'$ was the projected image, and $\bar{P}'$ is the average gray level of image $I(x,y)$.second order combined projected image, derived from the combination of Eqs.(2), substituted the original image for standard feature face recognition

$$P_{\alpha,\beta}(x,y) = \frac{P(x,y) + \alpha M_P(x,y) + \beta M_P'(x,y)}{1+\alpha+\beta} \quad (2)$$

2.3 SVD-P-based Algorithms

Singular Value Decomposition Perturbation (SVD-P) [15] implements singular value decomposition $P = U\Sigma V^T$ on the original image. The produced matrix Image $M_P = U\Sigma^n V^T$ was called projection bitmap. Then PCA was implemented on combined image obtained from Eqs. (1), where $n \in (1,2)$. Fig.2 (a-e) successively represented the original image, matrix image when $n = 5/4$, matrix image when $n = 3/2$, and the combined image with original image, matrix images when $n = 3/2$ and $n = 5/4$.

2.4 Geometric Transformation Techniques

Apart from (PC)2A and SVD-P, face image feature can also be enhanced by geometric transformation such as mirror, scaling ,translation and rotation Mirror: mirror image can eliminate the inferences brought by head rotation to face recognition in some degree and enhance the recognition results for person with posture variation,

Fig. 3: Original images and the mirrored images

due to the feature of basic symmetry for face. Specifically the images were mirrored perpendicular to central axis. Fig 3 shows part of images and their mirror images using FERET face database.

Rotation: Specifically, images were rotated certain angle in the image plane around the center, then the rotated image was equalized with the original image by interpolation and shear. The rotated images are usually larger than the original ones; the exceeded part is filled with 0 or 1. Part of the images from FERET face database was selected and rotated 5^o clockwise around the image center, the original images and the rotated images were as shown in Fig.4

Fig. 4: The original images and the rotated images (the first line were original image and the second line were images rotated 5^o)

Scaling: scale difference may exist between the images from the same person from the test samples, thus the scaling on original images is a techniques for increasing training samples. Specifically, shrink the original image with the factor of 0.9, and the blank part was filled with 0 or 1. Then original images were magnified with the factor of 1.1 and the exceeding parts beyond the original images were cut. Thus both magnified and shrunk virtual sample was obtained. The scaling factor is not necessarily set as 0.9 or 1.1, and can be set as 0.95 or 1.05 etc. in line with reality circumstances. Fig. 5 was part of the images from FERET face database and their scaled images. The scaling factor was 0.95 and 1.05.

2.5 Face Recognition Based on Image Enhancement and Geometric Transformation

The face reconstruction procedure is as follows: Eye was firstly rotated to the horizontal position, and then the

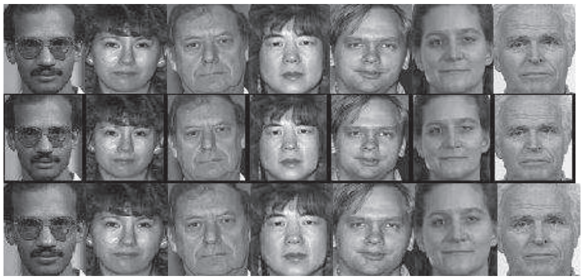


Fig. 5: The original, rotated and scaled images (the 1st,2nd and 3rd line were the original images, shrunk images with the factor of 0.95, and magnified images with the factor of 1.05

input image was adjusted in the front view through affine transformation, so as to compensate the deep posture variation of the input images. And then after scale normalization, 8 reconstructed images was got from every single sample by (PC)2A, E(PC)2A and SVD-P, and geometric transformation such as mirror, scaling , and rotation.

Table 1: Face reconstruction experimental procedure based on E (PC)2A and geometric transformation

Define the original image as,
Step 1: By adopting (PC)2A,where $\alpha = 0.25$, virtual sample $P1$ is generated. Step 2: By adopting E(PC)2A,where $\alpha = 0.25, \beta = 1.5$, virtual sample $P1$ is generated. Step 3: By adopting SVD-P, virtual sample $P1$ is generated. Step 4: By adopting geometric transformation, virtual sample $P1$ is generated: (1) Rotation: By rotating the original image by 5^o, virtual sample is generated; (2) Scaling: By magnifying and shrinking in the original image with the factor of 0.95 and 1.05, $P5, P6$ are generated, where blank part was filled by 0 with the factor of 0.95. (3) Mirror: By mirroring on the original image with $P4$, $P7, P8$ are generated.

3 LGBP Feature Representation

Gabor Wavelet Transform was firstly introduced by physicist D. Gabor during the analysis on the time domain of signal [20]. Daugman subsequently extended the 1D Gabor transformation to 2D condition [21].T. Lee found the application of Gabor Wavelet Transform in the representation of image[22]. The procedure of Gabor feature extraction on face image was as follows: convolution was firstly implemented on every face image, and then in every pixel point, the amplitude of post-convolution image was extracted as Gabor feature of Gabor wavelet.

LBP feature extraction method was first proposed by Ojala ect[23]. In the study of texture image classification, and the fundamental process of the LBP method for facial feature extraction is: for the position of each pixel in the facial image, compare the gray scale value of this point with its neighbors, and calculate the LBP eigenvalue according to the result of the comparison. Suppose $g_c(x,y)$ denote the gray level of an arbitrary pixel (x,y), Moreover, let $g_c^s(x,y)(s = 1,\cdots,S)$ denote the gray value of a sampling point in an evenly spaced circular neighborhood of S sampling points and radius R around point (x,y), then LBP features are calculated as follows:

$$LBP_{S,R}(x,y) = \sum_{s=1}^{S} h(g_c^s(x,y) - g_c(x,y)) \times 2^{s-1} \tag{3}$$

in which

$$h(g_c^s(x,y) - g_c(x,y)) = \begin{cases} 1 & h(g_c^s(x,y) - g_c(x,y)) \geq 0, \\ 0 & h(g_c^s(x,y) - g_c(x,y)) < 0. \end{cases} \tag{4}$$

Senechal et al. [9] and Wu et al. [18] proposed to use appearance features extracted in a multi-layer architecture, of which Local Gabor Binary Patterns (LGBP) is a prime example. LGBPs are extracted by ?rst creating a set of Gabor magnitude response images (one for every ?lter in a ?lter bank) and then applying an LBP operator to each of them. This has been shown to be very robust to illumination changes and misalignment [19].

4 Locality Preserving Discriminant Analysis (LPDA)

4.1 Locality Preserving Projections(LPP)

LPP, linearization of LE algorithm, overcomes the Out-of Sample problems and retains the inherent geometrical and local structure of data during dimension reduction . Sample set was assumed as $X = \{x_1, x_2, \ldots, x_N\}, x_i \in R^D$, with the existence of linear transformation $n = 5/4$. Transformation matrix W was obtained by the target function of maximization equation (5):

$$\max \sum_{i,j} (W^T x_i - W^T x_j)^2 S_{ij} \tag{5}$$

where S is a weight matrix which can be defined by ε-Nearest Neighbor:

$$S_{ij} = \begin{cases} \exp(-\|x_i - x_j\|/t), & \|x_i - x_j\|^2 < \varepsilon \\ 0, & except 0 \end{cases} \tag{6}$$

where $\varepsilon > 0$ is an enough small constant which is verified by experiment. Target function was gained by simple linear transformation:

$$\begin{aligned} S_{ij} &= \tfrac{1}{2}\sum_{i,j}(W^T x_i - W^T x_j)S_{ij} \\ &= \sum_{i,j} W^T x_i S_{ii} x_i^T W - \sum_{i,j} W^T x_i S_{ij} x_i^T W \\ &= \sum_{i,j} W^T x_i D_{ii} x_i^T W - \sum_{i,j} W^T x_i S_{ij} x_i^T W \\ &= W^T X(D-S)X^T W \\ &= W^T XLX^T W \end{aligned} \tag{7}$$

So the solution to the LPP can be converted into optimization problem as follows:

$$W = \arg\min_{w} W^T XLX^T W, s.t W^T XDX^T W = 1 \tag{8}$$

where D is $N \times N$ diagonal matrix $D_{ii} = \sum_j S_{ij}$; $\alpha = 0.25, \beta = 1.5$ is Laplacian matrix. The bigger D_{ii} is, the more important y_i symbolizes. The solution to Eqs.(8) can further be converted into solving the following eigenvalue problem:

$$XLX^T W = \lambda XDX^T W \tag{9}$$

4.2 Locality Preserving Discriminant Analysis

Locality Preserving Principal Component Analysis (LP-PCA) was proposed by integrating the idea of PCA and LPP local preservation. On the purpose of optimization reconstruction of sample, traditional (PC)2A got linear projection with minimum mean-square error between original sample and reconstructed sample. The reconstructed subspace with minimum variance is the one with maximum projection variances of data, equating to the solution to the following optimization function:

$$\max \sum_{i=1}^{N} \|y_i - \bar{y}\|^2 \rightarrow \frac{1}{2N}\sum_{i=1}^{N}\sum_{j=1}^{N}\|y_i - y_j\|^2 \tag{10}$$

The projection subspace of PCA was acquired from maximized distances between all the sample points. Same treatment was implemented for adjacent points and non-adjacent points, resulting unperceivable local structure of data. For better observing the relationship between LPP and PCA, [24] introduced the conception of complement. G^c was defined as the adjacent map of high-dimensional data set $X = \{x_1, x_2, \ldots, x_N\}, x_i \in R^D$, G^p as complement of G^c. Namely, G^p was connected only when the vertex i and j of G^c was not connected.

$$\max(\sum_{i,j=1}^{N}(W^T x_i - W^T x_j)^2 S_{ij}^p + \sum_{i,j=1}^{N}(W^T x_i - W^T x_j)S_{ij}^c) \tag{11}$$

where,d. A new optimized function was as follows:

$$\max \sum_{i,j=1}^{N}\|y_i - y_j\|^2 S_{ij}^p s.t. \sum_{i,j=1}^{N}\|y_i - y_j\|^2 S_{ij}^c = 1 \tag{12}$$

$$S^p = \begin{cases} 0, & \|x_i - x_j\|^2 < \varepsilon \\ 1, & else \end{cases} \tag{13}$$

where the definition of was the same as in Eqs.(6). LPPCA incorporated the idea of PCA and LPP local preserving, so as to preserve the original adjacent relationship of data set with adjacent point separated as far as possible in the projection space. While LPPCA, is still an unsupervised learning method, without using the class information of samples, from which the extracted feature in not favorable of classification. The LPDA in this article added the sample information based on LPPCA. Set l_i represent the class of sample the x_i, where $l_i \in \{1, 2, \ldots, c\}$; S_{ij}^c and S_{ij}^p was defined from Eqs.(12) respectively:

$$S_{ij}^c = \begin{cases} \exp() & \text{if } l_i = l_j \\ 0 & textrm\ else \end{cases} \tag{14}$$

$$S_{ij}^p = \begin{cases} 1 & \text{if } l_i \neq l_j \\ 0 & \text{else} \end{cases} \tag{15}$$

Optimization was achieved by incorporated $y_i = W^T x_i$ in to optimization Eqs.(12):

$$\begin{aligned} &\sum_{i=1}^{N}\sum_{j=1}^{N}\|y_i - y_j\|^2 S_{ij}^p \\ &= \sum_{i=1}^{N}\sum_{j=1}^{N}(W^T x_i - W^T x_j)^2 S_{ij}^p \\ &= W^T[\sum_{i=1}^{N}\sum_{j=1}^{N}(x_i - x_j)(x_i - x_j)^T S_{ij}^p]W \\ &= W^T(XD^pX^T - XS^pX^T)W \end{aligned} \tag{16}$$

Similarly, restraint condition can be simplified as follows:

$$\sum_{i=1}^{N}\sum_{j=1}^{N}\|y_i - y_j\|^2 S_{ij}^c = 1 \rightarrow W^T(XD^cX^T - XS^cX^T)W \tag{17}$$

where D^p, D^c are all diagonal matrixes, $D_{ii}^p = \Sigma_j S_{ij}^p, D_{ii}^c = \Sigma_j S_{ij}^c$,the optimization function of Eqs.(12) can be further simplified as:

$$\begin{aligned} &\max W^T(XD^pX^T - XS^pX^T)W\ s.t. \\ &W^T(XD^cX^T = XS^cX^T)W = 1 \end{aligned} \tag{18}$$

which was solved by Lagrange partial derivatives of:

$$\begin{aligned} L(W,\lambda) = {} & W^T(XD^pX^T - XS^pX^T)W \\ & -\lambda(W^T(XD^cX^T - XS^cX^T)W - 1) \end{aligned} \tag{19}$$

Partial derivatives of $L(W,\lambda)$ was solved as:

$$\begin{aligned} \frac{\partial L(W,\lambda)}{\partial W} = {} & 2(XD^pX^T - XS^pX^T)W \\ & -2\lambda(XD^cX^T - XS^cX^T)W \end{aligned} \tag{20}$$

Set $\frac{\partial L(W,\lambda)}{\partial W} = 0$,the solutions to Eqs.(12) can be further converted to the following eigenvalue problem

$$X(D^p - S^p)X^T w = \lambda X(D^c - S^c)X^T w \tag{21}$$

Fig. 6: face reconstructed images based on image enhancement and geometrical transformation (1st,2nd and 3rd are results from ORL, Yale and FERET respectively)

5 Experiment Result and Analysis

Three predominant international ORL face database [25], Yale face database [26] and FERET face database were adopted for validating the proposed protocol in this article. ORL database included 40 people with 10 images each; Yale database contained total 165 images, 15 people with 11 images each comprising different expressions and external conditions. FERET database consisted of 984 images in all, 246 people with 4 images each, which were all frontal or semi-frontal photos. Experiment procedures are as follows:
1Face reconstruction: every image was sampled with size of 32×32, a semi-front image, with neutral expression in normal light, was used as training samples, other images as test samples. Then face reconstruction was implemented by the procedure introduced in Section 1.5. Original images in Fig.8, selected from ORL, Yale and FERET face database and the virtual sample images were generated by the algorithm in Table 1. Original images were represented in the first column, and the subsequent columns were $P1 \sim P8$ respectively. Parameter $\alpha = 0.25$ was select for combined projection method; parameter $\alpha = 0.25, \beta = 1.5$ was select for enhanced; parameter 5^o was select for rotation of geometric transformation and the blank parts were filled with 0; the images were shrunk and magnified with factor of 0.95 and 1.05 for scaling of geometric transformation, the blank parts was filled with 0. (2) Feature representation: original face images and the 8 reconstructed images were pretreated into new training sample set, and every image from sample set was feature-extracted, where DCT feature, LBP feature and LGBP feature was extracted for comparison in this experiment. For the sake of minimum calculation quantity, 49 parameters was selected for global feature as representation of DCT feature; operator $LBP_{8,1}$ was adopted for feature extraction as representation of DCT feature, where 256 dimensional eigenvector was obtained for each image; as representation of Gabor feature, Gabor wavelet kernel with 5 dimension and 8 direction was adopted, and it was sampled by 10×10 sample factor. A $10 \times 10 \times 40 = 4000$ dimensional vector was finally got for a 100×100 image.
(3) Feature reduction: It consists of PCA techniques, LPP techniques, LPDA techniques; where the eigenvectors, corresponding to top d maximum eigenvalues from characteristic equation $S_w = \lambda_w$, were selected by PCA techniques.
(4) Class recognition: a face image, ready for recognition, was firstly feature-extracted by the characteristic algorithm from algorithm respectively, and was then projected to low-dimensional space by feature dimension reduction algorithm from algorithm. Finally, class recognition was implemented by Euclidean distance-based Nearest Neighbour Classifier.

Recognition results, shown In Table 2, were produced by single sample with PCA, LPP, LPP and LPDA using 3 face databases. Under the condition of single sample, the recognition rate was apparently very low. Among them, recognition rate for PCA and LPP is relatively low because of the unsupervised learning method which could hardly take full advantage of the class information of samples; while the performance was partially enhanced by algorithm of LGBP feature representation, especially in Yale database. Moreover, class information of samples was introduced for Local preserving algorithm, resulting much higher recognition rate than that of others.

Table 2: Comparisons of recognition rate among a variety of algorithms under the condition of single training sample

Algorithms	ORL	Yale	FERET
PCA	64.17	67.00	61.61
LPP	64.05	66.83	57.96
LPDA	68.78	69.05	66.13
Gabor+PCA	70.21	76.83	67.24
Gabor+LPP	72.78	77.08	65.51
LGBP+LPDA	73.56	77.43	66.04

Table 3 shows the experiment result under the condition of virtual sample using the same algorithm, from which improved performance was found by adding virtual samples than that under single sample condition using certain algorithm. This is due to the increased information favored recognition, where the recognition rate of LPDA algorithm was higher than that of LPP in 3 databases, with 3.3% heightened averagely. Thus validation of LPDA in this article was demonstrated, and the recognition rate was found 2% higher for LPP and LPDA algorithms integrated with LGBP feature. The max recognition rate was found as 91.56% in the case of using ORL with LGBP-featured LPDA, and the recognition rate was 27% higher for PCA compared with single sample condition. In this article, the feature representation performance of DCT feature, LBP feature and LGBP feature were compared by single sample with PCA, LPP, LPP and LPD using 3 face databases, as ORL, Yale and FERET, and compared with original images without any feature extraction simultaneously. Experimental results in

Table 3: Comparisons of recognition rate for a variety of algorithms after sample virtualization

Algorithms	ORL	Yale	FERET
PCA	68.05	81.33	68.49
LPP	72.31	79.33	67.34
LPDA	88.01	88.48	87.76
Gabor+PCA	87.22	88.00	86.83
Gabor+LPP	91.11	87.33	86.67
LGBP+LPDA	91.56	92.75	89.12

3 face databases were shown in Table 4 and Table 6, where recognition rates of any feature representation algorithms are all higher than that of original grey image direct dimension reduction method. The recognition rate of LGBP feature representation was higher since LGBP function may approximate the receptive field of visual cortical cell of mammals, reflecting the invariant information on face. This method is of certain robustness to light and posture, with favorable time domain localization feature meanwhile. Experiment results obtained by adopting original image, DCT feature, LBP feature and LGBP feature using 3 databases.

Table 4: Experimental results of feature representation algorithm using ORL face database

	Original image	DCT feature	LBP feature	LGBP feature
PCA	76.45	77.22	76.23	77.22
LPP	82.23	81.89	82.43	82.51
LPDA	88.01	88.93	89.36	91.56

Table 5: Experimental results of feature representation algorithm using Yale face database

	Original image	DCT feature	LBP feature	LGBP feature
PCA	80.12	80.47	80.78	81.00
LPP	84.32	84.96	85.47	85.96
LPDA	88.48	89.33	90.87	92.75

Table 6: Experimental results of feature representation algorithm using FERET face database

	Original image	DCT feature	LBP feature	LGBP feature
PCA	78.75	79.23	80.09	80.83
LPP	86.18	86.18	87.11	87.48
LPDA	87.76	88.04	88.46	89.12

6 Conclusions

This article proposed a single sample per person face recognition algorithm based on LPDA projection and LGBP. Firstly, sample reconstruction of single sample face image from geometric transformation combined with original training sample image, new sample set. The LGBP feature of every face image from sample set was subsequently collected and then dimensional reduction for high-dimensional LGBP eigenvector was implemented by LPDA. Lastly, the Classification for eigenvector with reduced dimensions was implemented by KNN algorithm. Experimental results from FERET Database, ORL Database and Yale Face Database demonstrate the validity of this algorithm on single sample face recognition. Although it is an effective idea by converting the single sample face reconstruction to multiple sample face recognition, the quality of face recognition results affect the accuracy of class recognition and generalization ability. The development of 3D face recognition techniques has provided an research area for single face recognition in recent years. When it comes to the face feature representation, the adopted features in this article are global feature of images which is insensitive to the local variance of expression, light and etc. for future work, coalesce of global and local feature of images can be taken into account for feature representation. For instance, feature representation was implemented after images blocking. In terms of face feature dimension reduction, the LPDA, proposed in this article, produced favorable recognition effect, and was applicable to situation of slow-varying posture and expression. Considering of the more complicated situation in the reality application, LPDA is still in need of improvement.

Acknowledgement

This work was supported by National Nature Science Foundation of China (No. 60972023), National Science and Technology Important Special Project (2011ZX03003-002 & 2011ZX03003-004).

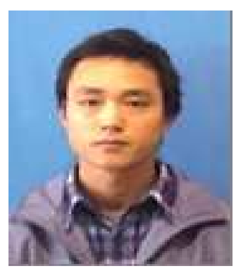
References

[1] Jain, A. K. , Fundamentals of digital image processing, Prentice-Hall, Inc, (1989).
[2] Tan, X., Chen, S., Zhou, Z.-H., and Zhang, F.: Face recognition from a single image per person: A survey, Pattern Recognition **39**, 1725-1745 (2006).
[3] Bledsoe, W. Man-machine facial recognition[J] **22**, (1966).
[4] Brunelli, R.,Poggio, T. Face recognition: Features versus templates[J]. Pattern Analysis and Machine Intelligence, IEEE Transactions **15**, 1042-1052 (1993).
[5] Manjunath, B.,Chellappa, R.,von der Malsburg, C. A feature based approach to face recognition [J], 373-378 (1992).

[6] Lam, K. M.,Yan, H. An analytic-to-holistic approach for face recognition based on a single frontal view [J]. IEEE Transactions on Pattern Analysis and Machine Intelligence **20**, 673-686 (1998).
[7] Poggio, T.,Beymer, D. Face Recognition From One Example View. In Massachusetts Institute of Tech Cambridge Artificial Intelligence lab, (1995).
[8] Vetter T. Learning novel views to a single face image [C]. Automatic Face and Gesture Recognition, Proceedings of the Second International Conference on. IEEE **10**, 22-27 (1996).
[9] Vetter, T. Synthesis of novel views from a single face image [J]. International Journal of Computer Vision **28**, 103-116 (1998).
[10] Zhang Lei,Wang Sen,Samaras D. Face synthesis and recognition from a single image under arbitrary unknown lighting using a spherical harmonic basis morphable model [C]. Processing of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, San Diego, USA, 209-216 (2007).
[11] Wu, J. ,Zhou, Z.-H. Face recognition with one training image per person [J]. Pattern Recognition Letters **23**, 1711-1719 (2005).
[12] Chen, S.C., Zhang, D.Q, Zhou Z.-H. Enhanced (PC)2A for face recognition with one training image per person[J]. Pattern Recognition Letters, (2006).
[13] Zhang D., Chen S., Zhou Z.-H.. A new face recognition method based on SVD perturbation for single example image per person[J]. Applied Mathematics and Computation, **163**, 895-907 (2007).
[14] M.P. Loh, Y.P. Wong, C.O. Wong. Facial expression recognition for E-learning systems using Gabor wavelet & Neural network. In: Proceedings of the 6th International Conference on Advanced Learning Technologies[C], Kerkrade, the Netherlands, 23-525 (2006).
[15] Yongmei Zhang, Zhangxing Ming, Yucong Guo. Face recognition base on low dimension Gabor feature using direct fractional-step LDA. In: Proceedings of International Conference on Computer Graphics, Imaging and Vision: New Trends[C], Guangzhou, China, 103-108 (2005):
[16] Buciu I., Kotropoulos C., Pitas I. ICA and Gabor representation for facial expression recognition. In: Proceedings of International Conference on Image Processing, Barcelona, Spain, **2**, 855-858 (2003).
[17] Colmenarez A., Frey B., Huang. T.S.. Embedded face and facial expression recognition.In: Proceedings of International Conference on Image Processing[C], Kobe, Japan, 633-637 (1999).
[18] J.B. Tenenbaum, V.de Silva and J.C. Langford. A global geometric framework for nonlinear dimensionality reduction[J]. Science **(**290), 2319-2323 (2000).
[19] Colmenarez A., Frey B., Huang. T.S.. Embedded face and facial expression recognition.In: Proceedings of International Conference on Image Processing[C], Kobe, Japan, 633-637 (1999).
[20] Gabor D., Theory of communication [J], J. Inst. Electr. Eng. **93**, 429-457 (1946).
[21] Daugman J. G., Uncertainty relation for resolution in space [J], J. Opt. Soc. Am. A, **2**, (1985).
[22] Lee T. S., Image representation using 2D Gabor wavelets [J], IEEE Transactions on Pattern Analysis and Machine Intelligence, **18**, 1-13 (1996).
[23] Ojala T., Pietikainen M., Maenpaa T., Multiresolution gray-scale and rotation invariant texture classification with local binary patterns [J], *IEEE Transactions on Pattern Analysis and Machine Intelligence*, **2002**, **24**, 971-987.
[24] Liu D. H., Lam K. M., Shen L. S. Optimal sampling of Gabor features for face recognition. Pattern Recognition Letters **25**, 267-276 (2004).
[25] http://www.cl.cam.ac.uk/research/dtg/attarchive/facedatabase.html.
[26] http://cvc.yale.edu/projects/yalefaces/yalefaces.html.

Minghai Xin received the M.S. degrees from Huaqiao University, Xiamen, China. Now, he is currently working toward the Ph.D. degree in the Research Centre for Learning Science, Southeast University, Nanjing, China. His research interests are in pattern recognition.

Yali Zhou received the M.S. degree in the Research Centre for Learning Science, Southeast University, Nanjing, China 2011. Her current research interests include affective computing and pattern recognition



Jingjie Yan received the M.S. degree in signal processing from China University of Mining and Technology, Xuzhou, China, 2009. Currently, he is a PH.D student with the School of Information Science and Engineering, Southeast University, Nanjing. His current research interests include affective computing and pattern recognition